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Developing Prediction Regions for a Time Series Model for Hurricane Forecasting

THESIS

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Developing Prediction Regions for a Time Series Model for Hurricane Forecasting

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Presented to the Faculty of the Graduate School of Engineering
of the Air Force Institute of Technology
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Master of Science in Space Operations

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Captain, USAF

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William Cheman

Table of Contents

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Abstract

In this thesis, a class of time series models for forecasting a hurricane's future position based on its previous positions and a generalized model of hurricane motion are examined and extended.

Results of a literature review suggest that meteorological models continue to increase in complexity while few statistical approaches, such as linear regression, have been successfully applied. An exception is provided by a certain class of time series models that appear to forecast storms almost as well as current meteorological models without their tremendous complexity.

A suggestion for enhancing the performance of these time series models is pursued through an examination of the forecast errors produced when these models are applied to historical storm tracks. The results uncover no patterns that can be exploited in developing an improved model and suggest that there are meteorological processes or factors at work beyond those that can be modeled with the available historical data base.

The statistical structure of the time series approach is exploited to develop a practical method for determining prediction regions which probabilistically describe a hurricane's likely future position. The Monte Carlo approach used to develop these prediction ellipses is seen to be applicable for predicting areas subject to risk from hurricane landfall.

Developing Prediction Regions for a Time Series Model for Hurricane Forecasting

I. Introduction

Hurricanes Andrew (1992) and Hugo (1989) are well known recent examples of the tremendous destructive capability of hurricanes. The difficulty that forecasters had predicting the time and location of landfall is remembered less, but had significant ramifications for those areas prepared and unprepared for the storms. Hurricane Emily (1993) is not remembered as well because it did not make landfall, but forecasters were uncertain of this until it curved eastward and moved away from land. These examples illustrate the need for accurate and timely hurricane forecasts, especially near the coast.

Hurricanes are part of a class of storms generally called tropical cyclones and tropical storms. In the Atlantic, they form off the west coast of Africa in warm equatorial waters from about June 1 to November 1. The first stage of development is called a tropical depression, when an area of organized circulation forms. Tropical depressions are characterized by poor boundary definition and sustained wind speeds of less than 34 knots. The next stage is tropical storm and is marked by an organized circulation pattern. Tropical storms are characterized by sustained wind speeds from 34 to 63 knots. The last stage is hurricane. A well defined three dimensional circulation structure is evident and sustained wind speeds are 64 knots or greater. Diminishing storms pass through these stages in reverse, usually after landfall or after they reach northern ocean waters too cool to add enough energy to sustain them.

Hurricanes are not differentiated further in this thesis. The terms hurricane, storm, and tropical storm will be used to mean all storm stages generally, when not otherwise obvious in context.

The National Hurricane Center (NHC) is the agency tasked with making official tropical cyclone forecasts. During an active storm, they provide six hour updates of forecasts out to 72 hours (twelve six-hour periods). Hurricanes have been hard to forecast because they do not consistently follow the same patterns that other weather systems do. The motivation for wanting to predict their motion is to minimize the damage from unexpected landfall.

A certain amount of position and intensity uncertainty arises from the scarcity of data about a particular storm, especially early in its formation and in remote areas of the ocean. "Best track" data is usually determined after the storm has ended and represents the best estimate of storm position developed from all available sources, such as satellite imagery and aircraft, ship, and sounding reports. Best track data is used when developing forecast models and testing their performance.

Over the past few years, the number of aircraft flights to get real-time position and other data has steadily decreased, primarily because of reduced budgets, not a reduction in the number of storms. Forecasters rely more and more on satellite imagery for real-time information about a hurricane, including position, intensity, and wind speed. Appendix A includes documentation of current methods to determine position and intensity from satellite data.

In this thesis, attention is focused on a class of time series models, developed by Curry (3) and extended by Mott (12), that forecast hurricane position based on a generalized model of hurricane motion and a particular hurricane's previous positions. The specific objectives of this research are to exploit this researcher's meteorological background to:

(*i*) review the current literature to summarise the current "state of the art" in hurricane forecasting;

(*ii*) develop, based on published results, an assessment of the relative performance of current methods for hurricane forecasting;

(*iii*) extend Mott's and Curry's efforts by developing a practical method for determining "prediction regions" which describe a hurricane's likely future position; and

(*iv*) assess the viability of improving Curry's and Mott's approaches by examining those storms that appear in some way "anomalous", that is, not well forecast by their models.

This thesis first examines the work accomplished by Curry and continued by Mott. Pertinent aspects of the model are discussed followed by a literature review covering other statistical and meteorological models developed since Curry's review in 1985. The models are then compared on the basis of their reported results.

An important contribution of this thesis is the adaptation of some theoretical results developed by Curry that enable one to develop prediction regions for a hurricane's future position which will help quantify the uncertainty associated with a forecast (3). In particular, a Monte Carlo approach is developed which sidesteps many of the complexities inherent in Curry's proposed methodology and which additionally has the potential to be used to develop landfall prediction regions.

This is followed by an analysis of the forecast errors when Mott's model is applied to historical data. In particular, those storms that appear to be potential outliers, producing much larger than average forecast errors, are identified and analyzed to see if they share any common characteristics (such as being early or late in the season) that could be easily incorporated into the time series models developed by Curry and Mott.

II. Time Series and Hurricane Forecasting

Box–Jenkins time series models provide one way to forecast random variables. They are distinguished from other models in their use of a combination of past values and observational errors to explain a present value or make a forecast. First Curry, then Mott used this approach to forecast hurricane tracks with favorable results. We review these models in the first three sections of this chapter.

Other statistical approaches, such as linear regression, have been applied to hurricane forecasting, generally with less success. Along with statistical models, the NHC uses a number of meteorological models to forecast hurricanes in an attempt to minimize the error from any one model (17). Some of these recent models, including NHC90, are discussed in later sections of this chapter. The chapter concludes with a comparison of the forecast errors published by Curry, Mott and the NHC.

2.1 Box–Jenkins Time Series Models

The fundamental basis for both Curry's and Mott's time series models of hurricane motion are the autoregressive–moving average (ARMA) models developed and explained by Box and Jenkins (1). In an ARMA model, a random variable, Y_t, is expressed as a weighted series of its values at past times, a weighted series of past errors, and the random "white noise" error associated with the current observation. The white noise errors are assumed to be independent and normally distributed with mean of zero and constant variance. An ARMA model is built empirically, but knowledge of the generating process sometimes helps in selecting the best model. The following sections describe the various types of univariate ARMA models where a random variable is explained only by its past values and its associated random errors.

2.1.1 Autoregressive Series. An autoregressive series has the form:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t + C \tag{1}$$

where the ϕ coefficients are the relative weights applied to past observations, e_t is a random error, and C is a constant for the process. The subscript t is the time index. The number of past observations, p, used in equation (1) is referred to as the order of the AR series.

2.1.2 Moving Average Series. A moving average series has the form:

$$Y_t = e_t - \theta_1 e_{t-1} - \cdots - \theta_{t-q} e_{t-q} + C \tag{2}$$

where the e's are the random errors that occurred at previous times, the θ 's are their relative weights, and C is a constant for the process. The MA is of order q and expresses Y_t as a function only of current and previous errors.

2.1.3 ARMA Models. An ARMA model incorporates elements of both AR and MA series and has the form:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} + C \tag{3}$$

and is said to be of order (p,q).

The order of an ARMA process is difficult to determine solely from a series of observations. Some knowledge of the underlying process is usually helpful. Most ARMA models can be adequately described by order (2,2) or less, even those which are generated by higher order processes (9:362). Examining the autocorrelation and partial autocorrelation functions of a postulated model will usually help indicate the order of an ARMA series. The autocorrelations give a quantitative indication of the interdependence between observations in the series while the partial autocorrelations

provide information about the order of the regressive component. Fitting an ARMA model to data is traditionally a somewhat complicated process which requires (i) identifying the order of the model, (ii) estimating its parameters, and (iii) assessing the adequacy of the fitted model. Makridakis, et al, give a provide a good description and illustration of this process (9). Several software packages are available that estimate the parameters of time series models from a series of data. A final check of the adequacy of the fitted model is provided by determining if the residual errors are statistically the same as white noise.

ARMA models can be developed only for series that have a constant, or stationary, mean and variance. A relatively straightforward way to induce stationarity in a non-stationary data series is to "difference" the data by subtracting each observation from its successor. The series of differences, or lags, is then used in the model rather than the raw data. Specifically, lag 1 is defined as observation 1 minus observation 2, lag 2 is observation 2 minus observation 3, and so on. Sometimes more than one difference is needed to induce stationarity, although each difference reduces the series length (and degrees of freedom) by one (10:45). Box and Jenkins refer to this aspect of time series modeling as integration, with the resulting model linearly approximating the differenced series. Curry found that the first differences of hurricane position were sufficiently stationary to model with ARMA models.

2.1.4 Transfer Function Models. An extension of univariate ARMA models is to include past values of one or more other explanatory variables in the model equation. The multivariate case has the form:

$$\begin{aligned} Y_t &= \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} \\ &+ \omega_0 X_t - \omega_1 X_{t-1} - \cdots - \omega_m X_{t-m} \\ &+ \zeta_0 Z_t - \zeta_1 Z_{t-1} - \cdots - \zeta_n Z_{t-n} + e_t \end{aligned} \tag{4}$$

where X and Z denote the other random variables, ω and ζ denote their respective weights and m and n are their respective orders.

2.2 Curry's Model

The purpose of Curry's research was to develop a quick and accurate means of forecasting hurricanes so that fewer people would have to evacuate and those who did would have greater forewarning in the event of hurricane landfall. Based on their relative simplicity, he chose a time series approach, eschewing the vastly more complex modeling schemes developed and used by the NHC (3:3).

Curry proposed a first–difference, bivariate, fifth–order AR model to model hurricane tracks. In his model, he used the series of first differences of latitude and longitude as predictors of each other. He further refined it as a "threshold model" by dividing it into 7 latitude bands, or thresholds. The model has distinct coefficients in each band. Forecasts are made for successive 6–hour periods, recursively using each forecast as a current position through 72 hours. In each latitude band, Curry's model has the form:

$$\begin{aligned} LA_t - LA_{t-1} &= \phi_{11,1}(LA_{t-1} - LA_{t-2}) + \phi_{11,4}(LA_{t-4} - LA_{t-5}) \\ &+ \phi_{12,1}(LO_{t-1} - LO_{t-2}) + \phi_{12,4}(LO_{t-4} - LO_{t-5}) \\ &+ C_1 + a_{1t} \end{aligned} \tag{5}$$

$$\begin{aligned} LO_t - LO_{t-1} &= \phi_{21,1}(LA_{t-1} - LA_{t-2}) + \phi_{21,4}(LA_{t-4} - LA_{t-5}) \\ &+ \phi_{22,1}(LO_{t-1} - LO_{t-2}) + \phi_{22,4}(LO_{t-4} - LO_{t-5}) \\ &+ C_2 + a_{2t} \end{aligned} \tag{6}$$

where LA_t and LO_t denote a storm's latitude and longitude at time t and the a terms are random errors. Note that Equations (5) and (6) are essentially AR transfer

function models with the same order applied to the first difference series of both latitude and longitude.

To develop this model, Curry started with the best track data from storms 1886-1983. Best track data is determined after all data sources report, usually after a storm is finished, and represents the best estimate of the actual path of a storm. For accuracy, he included only portions of storms of tropical storm strength (34 knot wind speed) or greater, storms in the Atlantic basin, and those that occurred after 1945. Position reports following landfall on the continental U.S. were also deleted since a storm's behavior over land can be expected to be different from that over water (3:134). The final data base contained 362 storm tracks with approximately 10,000 position reports.

Curry differenced this data after he assumed and confirmed that the storm tracks were non-stationary. That is, hurricane tracks clearly do not have a constant positional mean; they move across the ocean during their life and their positions do not vary randomly about a mean latitude or longitude. However, the first difference series of storm position appears to reasonably fit the criteria of mean and variance stationarity for time series modeling. That is, the change, or lag, in position from one period to the next appears to hover around a constant mean value. Curry identified nine stationarity categories based on the behavior of the first and second differences of latitude and longitude (3:37). He worked only with those storms that appeared to be "velocity" stationary under the assumption that storms in the other categories were not sufficiently stationary to be modeled with time series methods.

After further examining the autocorrelation and partial autocorrelation functions of successively higher order AR models, Curry found that an autoregressive transfer function model of order 5 best explained a storm's present position. The second, third, and fifth lags were generally weak and so were dropped from his final model (3:39), as seen in Equations (5) and (6).

To obtain forecasts from this model, a one–step ahead forecast position is based on the five most current position reports. To obtain a two–step ahead forecast, the one–step ahead forecast is treated as the last *observed* position and is used along with the four most recent position reports to obtain a pseudo one–step ahead forecast. Forecasts for lead times up to twelve steps ahead are computed in a similar manner (3:65).

Since the general motion of a storm changes with latitude, Curry subdivided the model into latitude bands in which the model coefficients (ϕ's) differ. When a forecast crosses a latitude threshold, coefficients for the new band are used for all forecasts in the new band. Great circle distance between the forecast and best track positions is reported as the forecast error in nautical miles (nmi), or kilometers (km) (17:526). The same error is reported by the NHC. Curry's model and coefficients are included in Appendix B.

To test the validity of his model, Curry calculated the model coefficients, then singly removed each storm from the data base and recalculated the model coefficients. Hypothesis tests showed no statistical differences in the coefficients were introduced by any one storm. Finally, he validated the model with a set of five storms. His forecast results for these five storms compared favorably with the official NHC forecasts for the same storms. Curry also developed theoretical expressions for "confidence ellipses" as functions of the model coefficients which probabilistically describe the area where a storm's future position is likely to be. These are discussed in following chapters.

2.3 Mott's Model

Following Curry's threshold ARMA approach, Mott developed a trivariate model that added maximum sustained wind speed as an explanatory variable (12).

In each latitude band, the model is:

$$\begin{aligned}
LA_t - LA_{t-1} &= \phi_{11,1}(LA_{t-1} - LA_{t-2}) + \cdots + \phi_{11,5}(LA_{t-5} - LA_{t-6}) \qquad (7)\\
&+ \phi_{12,1}(LO_{t-1} - LO_{t-2}) + \cdots + \phi_{11,5}(LO_{t-5} - LO_{t-6})\\
&+ \phi_{13,1}(WS_{t-1} - WS_{t-2}) + \cdots + \phi_{13,5}(WS_{t-5} - WS_{t-6})\\
&+ C_1 + a_{1t}\\
LO_t - LA_{t-1} &= \phi_{21,1}(LA_{t-1} - LA_{t-2}) + \cdots + \phi_{21,5}(LA_{t-5} - LA_{t-6}) \qquad (8)\\
&+ \phi_{22,1}(LO_{t-1} - LO_{t-2}) + \cdots + \phi_{22,5}(LO_{t-5} - LO_{t-6})\\
&+ \phi_{23,1}(WS_{t-1} - WS_{t-2}) + \cdots + \phi_{23,5}(WS_{t-5} - WS_{t-6})\\
&+ C_2 + a_{2t}\\
WS_t - WS_{t-1} &= \phi_{31,1}(LA_{t-1} - LA_{t-2}) + \cdots + \phi_{31,5}(LA_{t-5} - LA_{t-6}) \qquad (9)\\
&+ \phi_{32,1}(LO_{t-1} - LO_{t-2}) + \cdots + \phi_{32,5}(LO_{t-5} - LO_{t-6})\\
&+ \phi_{33,1}(WS_{t-1} - WS_{t-2}) + \cdots + \phi_{33,5}(WS_{t-5} - WS_{t-6})\\
&+ C_3 + a_{3t}
\end{aligned}$$

where LA and LO are latitude and longitude, WS is wind speed, ϕ's are the model coefficients, C's are constants and the a terms are random errors.

Starting with the complete data set through 1989, Mott reduced it similarly to Curry by eliminating storms that occurred before 1945, and positions observed after landfall. A departure from Curry was retaining data of tropical depression strength. This was useful for developing a model for all stages of storms since one cannot precisely forecast when a storm will change above or below tropical storm strength. It also allows forecasts to be made earlier in a storm's development. Including this data provides confidence that the resulting model also applies to both strengthening and weakening storms.

2.3.1 Stationarity. Since a goal of Mott's research was to create a model valid for all hurricanes, he was unwilling to limit his efforts to only one stationarity category as Curry did. Further, Mott noticed most storms rarely accelerated for very long and ultimately returned to what Curry termed velocity stationary. In other words, it was difficult to objectively categorize storms into one of Curry's stationarity categories since storms appeared to change category over time. He assumed that the probability of a storm's fluctuation from its mean level was the same at all times, and this allowed the development of a model with fixed coefficients to be developed, regardless of stationarity category.

2.3.2 Modeling Scheme. Mott constructed a variety of univariate, bivariate, and trivariate models on which he based his coefficient calculations. He used SAS statistical software routines, including backward and stepwise regression, to calculate the model coefficients and their statistical significance. Then, each model was used to forecast storm motion for each data point and great circle distance error statistics were collected. The results indicated that the best model was trivariate, using past latitude, longitude, and wind speed information to forecast each component. Mott's final model and coefficients are also included in Appendix B.

2.3.3 Outliers. Both Curry and Mott noted that anomalous tracks occasionally occurred and that these tracks gave the greatest forecast errors. Both were concerned about the possible bias this data introduced into their respective models because the behavior of these storms might not be representative of typical hurricane tracks. Part of this research is devoted to determining identifying characteristics of these storm tracks and is discussed in following chapters.

2.4 Other Models

Other approaches to hurricane modeling and forecasting are documented in the meteorological literature. Different statistical approaches have been applied to developing hurricane forecasting models, but the majority of models use meteorological input, some on a very large scale. This section briefly discusses some of these other models and their relevance to a time series approach.

2.4.1 Statistical Models. In "An Analysis of the Error Characteristics of Atlantic Tropical Cyclone Track Prediction Models", James Kroll examines a number of hurricane forecast models and their characteristics (7). He develops a Combined Confidence Weighted Forecast model that assigns relative weights to a number of existing forecast models based on their forecast errors (7:43-44). This amounts to the development of a linear program for minimizing the aggregate error of the (NHC) models. He also attempts to develop linear regression models using a number of explanatory or predictor variables, such as vorticity, storm speed, and Julian date, among others to forecast hurricane position. He concludes that these factors are not linearly related to storm track (7:99); that is, a linear regression model using these factors does not produce good track forecasts. This reinforces our rationale for developing a time series model.

Merrill develops a linear regression model to predict tropical cyclone intensity changes (11). Currently, NHC uses SHIFOR (*S*tatistical *H*urricane *I*ntensity *FOR*ecast), a statistical model that incorporates initial position, date, location, motion, and intensity change of a storm to predict future intensity changes. He tests variables such as sea surface temperature, wind information at various levels, Julian date, and previous intensity changes for significance. He also tests "custom" products of the variables to see if they indicate whether non–linear predictors of intensity change are useful. Merrill's results offer slight improvement over the current SHIFOR intensity model, but they are not statistically significant (11:24). He concludes

tropical cyclone intensity changes are influenced by environmental conditions, but the relationships are weak and their usefulness as objective forecasting aids is limited (11:23). This shows that linear regression models are also not useful for forecasting change in tropical cyclone intensity.

The STRIKPA model explained by Jarrell generates a hurricane forecast bulletin using three difficulty classes (5). Instantaneous and time integrated landfall probabilities are generated, analogous to the STRIKPA model used for Pacific storms. Use of these difficulty classes is unclear and the reference explaining them is unavailable, so our ability to assess the utility of this model is hampered.

In his thesis, "A Kalman Filter With Smoothing for Hurricane Tracking and Prediction", Asim Mutaf presents a Kalman filter model to forecast smoothed hurricane tracks (13). This method was also applied to hurricane wind speed, but necessary wind speed data was frequently unavailable with the position data which resulted in a frequently unstable model (13:46). Model results were favorable for the two control storms presented, but a larger data base is necessary to validate this technique. Mutaf mentions this method is particularly useful for storms with scarce previous track data, as might happen in some Pacific storms.

2.4.2 Meteorological Models. The vast majority of hurricane prediction models use large amounts of observed and modeled weather data and meteorological equations. The NHC generates and tests most of these for possible use in operational hurricane forecasting. Currently, they use seven different models simultaneously to forecast a storm, then a human forecaster subjectively blends these forecasts to arrive at the official forecast. This is explained in "Models for the Prediction of Tropical Cyclone Motion over the North Atlantic: An Operational Evaluation" by Neumann and Pelissier (17). Since this report, a new model, NHC90, has been developed. It incorporates a variety of meteorological information including climatological and persistence data, and observed and forecast deep layer geopotential heights (similar

to the heights of pressure levels). It is based on a previous model developed in 1983 called NHC83. During the trial phase of NHC83, a number of problems in the model were identified. These were corrected and incorporated into the new model NHC90. Input, output and various performance considerations are described in "A Revised National Hurricane Center NHC83 Model (NHC90)" (16). Unfortunately, the researchers devised a new way of classifying storms into north and south zones that obscures similarities with previous results. As well, the period of the test data is different from other research.

Franklin and DeMaria indicate the importance of using accurate and extensive wind and pressure data for hurricane forecasting in "The Impact of Omega Dropwindsonde Observations on Barotropic Hurricane Forecasts" (4). Dropwindsondes consist of mostly the same instruments as found on weather balloons (without the balloon) that are dropped from aircraft near or in hurricanes. During their descent to the earth, they transmit real–time meteorological observations that can be input into forecast models. Barotropic models are based on a simplified atmospheric structure where temperature and pressure gradients are colinear. Some barotropic models are used in the NHC modeling scheme. More extensive wind and pressure input for these models, available from dropwindsondes, markedly improves their performance. A significant forecast improvement (10 to 15 % reduction in error) resulted from the use of dropwindsonde data, but the authors note that there is currently no theoretical basis to optimise the data collection pattern. They also make the point that the cost of getting the data is more than offset by increased forecast accuracy and resultant decreased impact possible from fewer false alarms and unnecessary evacuations (4:390).

Kurihara, et al, describe the application of a movable mesh model to forecast the 1985 hurricane Gloria (8). Mesh refers to an arbitrarily placed grid pattern that specifies points on the earth's surface where weather information is interpolated. A movable mesh uses the same grid at progressively different locations, based on storm

movement. A fine mesh with a grid spacing of $\frac{1}{6}^{o}$ and two coarse meshes of 1^{o} and $1\frac{1}{2}^{o}$ were used. A combination of coarse and fine mesh models was used to capture and forecast elements of the storm with favorable results (8:2189). However, an important caveat is brought up, namely, the selection and application of which mesh and when to use it is highly subjective and has a large impact on the results. As well, this approach has been applied only to a single storm after the fact and can't yet be considered to be generally valid for other storms.

2.5 Comparison of Published Results

Curry, Mott, and NHC use great circle distance to report errors between observed and forecast positions. It can be computed from:

$$d = 60cos^{-1}[sin(LA_f)sin(LA_o) + cos(LA_f)cos(LA_o)cos(LO_o - LO_f)] \qquad (10)$$

where d is in nautical miles, subscript f denotes the forecast obtained from the model and subscript o denotes the observed position from the best track data. The results are shown in Table 1 in nautical miles and corresponding kilometers in parentheses.

NHC and Curry used data from storms of tropical storm strength or greater. Mott also included data from the tropical depression stage. Note that the periods of analysis are also different. As a result, a different combination of storms was used by each source. Curry and NHC divide the number of initial storm positions approximately in half by creating north and south zones such that roughly as many storms start above the dividing latitude as below. NHC also reports model error trends using a rotated coordinate system. Errors are further characterized by NHC as slow or fast, and right or left of track using track–oriented coordinates (17). Comparable summaries were not available for use with the Curry or Mott models and so are not reported here.

		Forecast Period (hours)							
		12		24		48		72	
Curry:	10-15N			57.9	(107)	131.9	(244)	204.8	(379)
1945-1983	15-20N			70.6	(131)	154.6	(287)	253.0	(469)
	20-25N			76.6	(142)	165.6	(307)	260.1	(482)
	25-30N			96.2	(178)	203.2	(377)	293.9	(545)
	30-35N			107.7	(200)	242.4	(449)	358.6	(664)
	35-40N			121.0	(224)	267.5	(496)	391.8	(726)
	40-45N			138.7	(257)	269.8	(500)	206.3	(382)
	overall			109.8	(203)	214.6	(398)	312.0	(578)
N zone	25-45N			126.5	(234)	251.0	(465)	351.5	(651)
S zone	10-25N			92.4	(171)	177.9	(330)	272.2	(504)
Mott:	10-15N	23.6	(43.7)	62.3	(115)	151.9	(281)	248.9	(461)
1945-1988	15-20N	31.3	(58.0)	77.6	(144)	186.0	(344)	301.0	(557)
	20-25N	35.2	(65.2)	87.8	(163)	219.0	(406)	363.8	(674)
	25-30N	39.9	(73.9)	106.5	(197)	271.8	(503)	429.5	(795)
	30-35N	47.6	(88.2)	127.1	(235)	310.6	(575)	496.1	(919)
	35-40N	58.8	(109)	140.4	(260)	320.4	(593)	526.8	(976)
	40-45N	68.4	(127)	175.0	(324)	495.6	(918)	926.4	(1716)
	overall	41.3	(76.5)	103.3	(191)	242.7	(449)	376.1	(697)
NHC:	overall	43.2	(80)	91.8	(170)	184.1	(341)	275.4	(510)
1983-1988	>22.5N	48.6	(90)	104.2	(193)	193.8	(359)	321.3	(595)
	<22.5N	32.9	(61)	68.0	(126)	169.5	(314)	230.6	(427)
1973-1979	overall	51.4	(95.2)	110.1	(204)	244.0	(452)	362.0	(671)
	>24.5N	57.9	(107)	131.3	(243)	304.4	(564)	421.0	(780)
	<24.5N	42.8	(79.3)	84.5	(157)	179.2	(332)	317.3	(588)

Table 1. Hurricane Model Forecast Errors, nmi (km)

At first glance, it would appear from Table 1 that the forecasts generated by the NHC are the best since their average reported errors over all regions are generally smaller than those reported by Curry or Mott. For the same reasons, Curry's model appears to perform slightly better than Mott's. Unfortunately, the differences in the data sets used in computing the these averages make such conclusions tenuous at best. In particular, NHC and Curry use data from storms of tropical strength or greater, while Mott includes tropical depressions as well. Perhaps more significantly, the periods of analysis are also different, that is, different combinations of storms are used by each source.

The effect of including tropical depressions seems to inflate the average errors. This is shown by Mott, who also computes forecast error for Curry's model using his own (unfiltered) data base. As seen in Table 2, average overall forecast errors for Curry's model are larger when it is applied to all storm stages from 1945 to 1983 (including tropical depressions as computed by Mott) than when tropical depressions are excluded (as computed by Curry). The implication seems to be that tropical depressions are more unpredictable than their stronger counterparts. We study this in more detail in the next chapter.

	Forecast Period (Hours)			
	12	24	48	72
Computed by Curry		109.8	214.6	312.0
Computed by Mott	48.7	120.0	269.8	406.7

Table 2. Average Overall Forecast Errors for Curry's Model

Mott's results should also, perhaps, be viewed somewhat suspiciously as evidenced in Table 3, which summarizes Mott's published results over a number of time periods. Clearly, something is amiss since some of the reported averages from 1945 to 1988 are smaller than either of the corresponding averages computed from 1945 to 1983 and 1984 to 1988. One would expect the 1945 to 1988 average to be between the others.

		Forecast Period (Hours)			
		12	24	48	72
Curry's Model	1945-83	48.7	120.0	269.8	406.7
	1984-88	51.8	128.7	287.1	409.8
	1945-88	48.7	119.8	268.9	404.6
Mott's Model	1945-83	41.5	103.5	242.2	375.8
	1984-88	44.3	113.8	267.6	415.0
	1945-88	41.3	103.3	242.7	376.1

Table 3. Average Overall Forecast Errors with Tropical Depressions (computed by Mott)

III. Hurricane Prediction Regions

This chapter describes the methods and rationale by which we attempt to further Mott's time series hurricane forecast model to include probabilistic prediction regions for future storm position. Since Mott's final model is the basis of all manipulations and calculations, a first step is to compare the difference in forecast errors between using tropical depression data in the model, as Mott did, and removing this data, as NHC does. Once the effect of this is established, the transition from a simple, rectangular prediction region to a bivariate elliptical region is developed. A Monte Carlo simulation is used to generate these probability regions and the utility of this method is demonstrated.

3.1 Tropical Depression Data

One of Mott's goals was to develop a model that was useful for forecasting all stages of tropical cyclones, regardless of strength or stationarity category. He noted that it was nearly impossible to tell when or for how long a particular storm would (or wouldn't) increase or decrease in intensity. Thus, he favored including all data from the storms in the database, regardless of wind speed. Mott included data from tropical depressions, that is, storms and storm segments with sustained winds of less than 34 knots in developing his models. Because they are generally less organized, their motion can be expected to be influenced more by external meteorological conditions than are stronger tropical storms and hurricanes (2:314).

On the other hand, no other researchers include tropical depression data in their model development or forecast error reports, and we wished to check if including this data may have biased both Mott's model and his reported error statistics. This data would need to be removed and the model coefficients recalculated if Mott's results were statistically different without tropical depression data.

Position reports from storms with wind speeds less than 34 knots thus were filtered from the storm database. All data greater than tropical storm strength was retained; only points with wind speed below 34 knots were removed. Mott's final model was then run first with all the original data, then with the filtered data. Error statistics were generated for each database and compared. Results from the model with the unfiltered data are shown in Table 4 and results with the filtered data are shown in Table 5. Differences are slight, and hypothesis tests confirm the differences are statistically insignificant at the 99% level.

These results imply that the model coefficients apply equally well to tropical depressions, tropical storms, or hurricanes and that inclusion of the tropical depression data does not substantially bias Mott's reported measures of forecast accuracy. Since we agree with Mott that this data ought to be included in developing a viable model, this research proceeded without recomputing the model coefficients.

3.2 Prediction Region Development

An advantage that statistical models have over meteorological models is that they naturally provide a means of describing a region within which the model would predict a storm would likely be. Assuming that the random errors contained in our model have a bivariate normal distribution, it follows that the errors associated with a storm's forecast position also have a bivariate normal distribution and the latitude and longitude of its future position are each normally distributed. One can then easily construct separate 100(1-α) % prediction intervals for a storm's future latitude and longitude if the variances of the forecast errors are known or can be estimated. In particular, if we let $\widehat{LA_{t+l}}$ and $\widehat{LO_{t+l}}$ denote the forecasted latitude and longitude at l time steps in the future, and let σ_1^2 and σ_2^2 denote the variances of the l–step ahead forecast errors in the latitude and longitude directions, then

OVERALL FORECAST ERROR SUMMARY					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	7069.	13.8837	22.1548	0.1944	5.8290
12HR	6734.	41.4018	39.2187	0.2803	9.8451
24HR	6063.	103.5616	78.0337	-0.0430	15.5701
48HR	4743.	243.2267	163.4678	-1.9407	21.7397
72HR	3639.	376.3317	239.5433	-3.9957	24.5875

FORECAST ERRORS FOR LAT BAND 1					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	573.	6.6948	12.2494	0.1686	5.1662
12HR	560.	23.7970	22.0288	0.2158	9.1464
24HR	539.	62.5049	52.7147	0.1717	16.1079
48HR	495.	152.6815	108.1897	-1.3243	25.9912
72HR	454.	251.3975	165.0699	-3.2103	30.3096

FORECAST ERRORS FOR LAT BAND 2					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1093.	9.7225	26.8267	0.3743	6.7017
12HR	1064.	31.3281	39.3789	0.7524	11.6103
24HR	1008.	77.7159	56.5139	1.6058	18.4564
48HR	909.	186.4410	103.7929	1.4624	24.9959
72HR	820.	302.0040	166.7822	-0.0922	27.5448

FORECAST ERRORS FOR LAT BAND 3					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1325.	11.5459	18.9466	-0.1292	6.1360
12HR	1302.	35.0921	35.6572	-0.3335	10.8593
24HR	1253.	87.7139	69.4099	-1.1214	17.6346
48HR	1114.	220.0129	154.8390	-2.8742	23.5915
72HR	925.	366.1059	250.1919	-3.8596	25.7184

FORECAST ERRORS FOR LAT BAND 4					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1485.	12.6875	18.8105	0.3545	6.8699
12HR	1423.	39.9202	33.9791	0.5239	11.0885
24HR	1280.	106.5221	74.0204	-0.2781	16.1690
48HR	1028.	270.3296	168.5778	-3.8992	20.4066
72HR	784.	426.6084	242.8052	-7.7132	20.3057

FORECAST ERRORS FOR LAT BAND 5					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1212.	14.8686	19.9300	0.1229	4.5284
12HR	1176.	47.7177	37.2576	0.1059	7.4863
24HR	1108.	127.2018	81.5491	-0.1403	11.5795
48HR	825.	311.9072	174.6172	-2.0081	15.0116
72HR	515.	499.6970	252.0175	-4.4721	17.3789
FORECAST ERRORS FOR LAT BAND 6					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	946.	20.4669	25.1238	0.2415	4.4064
12HR	900.	58.7448	47.8595	0.5059	7.2818
24HR	705.	141.7330	94.0775	0.0713	11.1526
48HR	334.	333.3453	185.2412	-3.1191	15.9542
72HR	129.	524.4794	271.5908	-9.1660	18.1830
FORECAST ERRORS FOR LAT BAND 7					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	435.	27.9528	27.7191	0.3133	5.3766
12HR	309.	66.8525	43.9893	0.2426	8.0306
24HR	170.	169.1263	87.1928	-0.6208	11.6383
48HR	38.	445.2230	245.4738	0.7943	12.8953
72HR	12.	798.6640	306.7503	7.9552	10.9006

Table 4. Forecast Errors With Tropical Depression Data

OVERALL FORECAST ERROR SUMMARY					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1471.	12.4231	19.0288	0.2165	6.4126
12HR	1385.	40.1329	36.3064	0.0662	10.0711
24HR	1209.	100.4248	73.5527	-0.9955	15.5174
48HR	877.	233.9071	151.9349	-5.6711	19.4610
72HR	654.	380.6521	231.5491	-8.9159	20.9687

FORECAST ERRORS FOR LAT BAND 1					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	107.	5.4433	11.3793	-0.2193	3.7339
12HR	106.	22.9768	23.1243	-0.6172	6.1661
24HR	103.	64.2772	48.7063	-2.0682	9.6871
48HR	97.	178.2417	106.7414	-6.5209	14.9612
72HR	94.	313.8691	155.1456	-10.2317	17.0372

FORECAST ERRORS FOR LAT BAND 2					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	191.	8.5425	13.8736	0.5217	7.3472
12HR	180.	29.9391	23.6592	0.2441	12.1232
24HR	162.	76.4328	51.2605	-1.3900	19.2433
48HR	130.	189.4273	102.6489	-11.1588	22.0947
72HR	115.	294.7719	130.8438	-18.9672	21.9406

FORECAST ERRORS FOR LAT BAND 3					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	258.	10.7047	15.5602	-0.8213	4.9106
12HR	252.	34.4744	28.1402	-1.9214	9.5103
24HR	237.	87.4906	55.9169	-4.0593	18.5607
48HR	195.	219.4733	137.2368	-9.2227	22.9932
72HR	159.	372.8253	231.7108	-8.6047	23.5791

FORECAST ERRORS FOR LAT BAND [illegible]					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	335.	10.5417	16.0678	0.3530	9.3718
12HR	321.	36.8703	31.6514	0.3739	13.6585
24HR	279.	97.5051	69.1440	-0.9616	18.1356
48HR	225.	249.4264	171.8977	-3.6698	19.5612
72HR	169.	432.9576	264.6495	-3.7649	19.2547

FORECAST ERRORS FOR LAT BAND 5					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	276.	12.7738	19.3964	0.6836	4.6113
12HR	262.	44.6530	37.0867	1.0515	6.5987
24HR	246.	119.4761	79.2823	1.5729	9.9131
48HR	176.	281.8597	167.98[illegible]	-0.1085	14.1480
72HR	105.	448.7641	267.2599	-4.2559	17.0769
FORECAST ERRORS FOR LAT BAND 6					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	200.	18.0333	25.6591	0.3508	4.4162
12HR	192.	54.6750	48.5064	0.6810	7.5500
24HR	149.	133.1868	97.1556	0.5706	11.5582
48HR	51.	267.9384	167.6344	-4.9871	14.8084
72HR	12.	497.8853	261.2467	-19.7256	20.9371
FORECAST ERRORS FOR LAT BAND 7					
FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	104.	25.3356	25.1876	0.7421	5.4312
12HR	72.	69.9979	48.7447	0.9876	7.4625
24HR	33.	158.6578	85.7521	-0.2092	4.7570
48HR	3.	343.6791	11.8737	2.3850	3.4518

Table 5. Forecast Errors Without Tropical Depression Data

100(1-α) % prediction intervals on a storm's future position will be given by

$$\widehat{LA_{t+l}} \pm z_{\alpha/2}\sigma_1$$

$$\widehat{LO_{t+l}} \pm z_{\alpha/2}\sigma_2$$

where $z_{\alpha/2}$ is a critical value from a standard normal distribution corresponding to the specified significance level, α. If latitude and longitude were independent, one would then have a rectangular prediction region with probability of $100(1-\alpha)^2\%$ of a forecast falling inside of it.

Unfortunately, latitude and longitude can't be considered independent for this purpose because future storm coordinates are constrained by the physical process of storm motion. Clearly, for any given latitude, a storm can't randomly move to any longitude and vice versa. Additional effort is needed to calculate a prediction region. In particular, according to standard statistical results [see, for example, Johnson and Wichern (6)], if a storm's future latitude and longitude at l–position reports ahead have a bivariate normal distribution, we can write:

$$\begin{aligned} P\Bigg[\frac{1}{1-\rho^2}\Bigg\{\left(\frac{LA_{t+l}-\widehat{LA_{t+l}}}{\sigma_1}\right)^2 + \left(\frac{LO_{t+l}-\widehat{LO_{t+l}}}{\sigma_2}\right)^2 \\ -2\rho\left(\frac{LA_{t+l}-\widehat{LA_{t+l}}}{\sigma_1}\right)\left(\frac{LO_{t+l}-\widehat{LO_{t+l}}}{\sigma_2}\right)\Bigg\} \le \chi^2_{2,\alpha}\Bigg] = 1-\alpha \end{aligned} \tag{11}$$

where LA_{t+l} and LO_{t+l} are the storm's future latitude and longitude, ρ is the correlation between them, σ_1 and σ_2 are their respective standard deviations, $\widehat{LA_{t+l}}$ and $\widehat{LO_{t+l}}$ are their respective means, and $\chi^2_{2,\alpha}$ is the critical value from a Chi–square distribution with two degrees of freedom at the desired significance level.

3.2.1 Curry's ψ Method. Curry develops a series of equations to define a prediction region based on his so–called ψ form of the ARMA model equations in

his dissertation (3). In order to calculate the prediction ellipses, the model equations need to be manipulated into this form. This involves algebraically rewriting his bivariate AR models as infinite-order MA models whose coefficients are denoted by ψ's. Once these are derived for the model equations within each latitude band, expressions for the desired variances and correlation can be developed. Within each latitude band, these computations are rather tedious, but straightforward. They become much more complicated when the storm's forecasted track crosses latitude bands and require a complicated updating scheme to be used. In particular, when forecast positions cross a threshold, ψ values of the previous band are used for observations and forecasts in the old band and values of the new ψ's are used for forecasts in the new band, and the computations become somewhat intractable (3:79).

Curry uses the resultant expressions to generate confidence ellipse axes (3:68-75). The equations are based on the one-step ahead forecast errors. These errors are assumed to have a multivariate normal distribution because each is random "white noise" error. Curry's resulting prediction ellipse has essentially the same form as equation (11), but erroneously uses a critical value from a normal distribution, rather than the appropriate Chi-square distribution (6:126).

In order to apply these results to Mott's model, an arduous reworking of the equations would be required to account for three explanatory variables, instead of the two, latitude and longitude, that Curry uses. This would be time consuming to develop and check, as well as code. We thus consider a more appealing and intuitive approach.

3.2.2 Monte Carlo Simulation. An alternative to the deterministic computation of the desired variances and correlation coefficient is to run the model numerous times with simulated random errors to generate the statistical equivalent to the solution of Curry's ψ equations. This is conceptually simpler, quicker to code, and arrives at approximately the same results. Sample statistics are used to esti-

mate the needed variances and correlation coefficient. It requires relatively greater amounts of processing to obtain solutions, but is still a reasonable approach to use operationally.

This method proceeds by generating a number of simulated storm tracks using the model's defining equations (given by Equations 7–9) with simulated values from a normal distribution used to represent the random model errors. Within each latitude band, these model errors are each assumed to have a mean of zero and a variance equal to the mean squared error found by Mott in fitting his model equations. The correlation between the latitude and longitude errors is assumed to be zero since Curry's results suggest this is a reasonable first approximation (3). (Curry's results show that the correlations within each latitude band are small. In most cases, we would fail to reject the hypothesis that the correlation was zero at, say, a 5 % level of significance. Because the correlations are all relatively small, it is doubtful that accounting for them explicitly would substantially alter the resulting prediction regions.) The FORTRAN code to accomplish this is included in Appendix C.

In order to produce a prediction ellipse, the l–period ahead position from each simulated storm track is recorded and these are then used to estimate the variances of the l–position ahead latitude and longitude forecast errors as well as the correlation between them. These, in turn, are used in defining the equation of the corresponding ellipse.

In our code, 200 simulated storm tracks are generated each time a prediction ellipse is desired. If the number of such tracks is large (as we assume in this case), then the sample variances will approximate the actual variances and the use of Chi–square critical values remains valid. Otherwise, critical values from Hotelling's–t statistic should be used (6). Figure 3 shows an example of the 24–hour 99% forecast ellipse and corresponding probability rectangle for Hurricane Hugo (1989) approximately 24 hours before landfall.

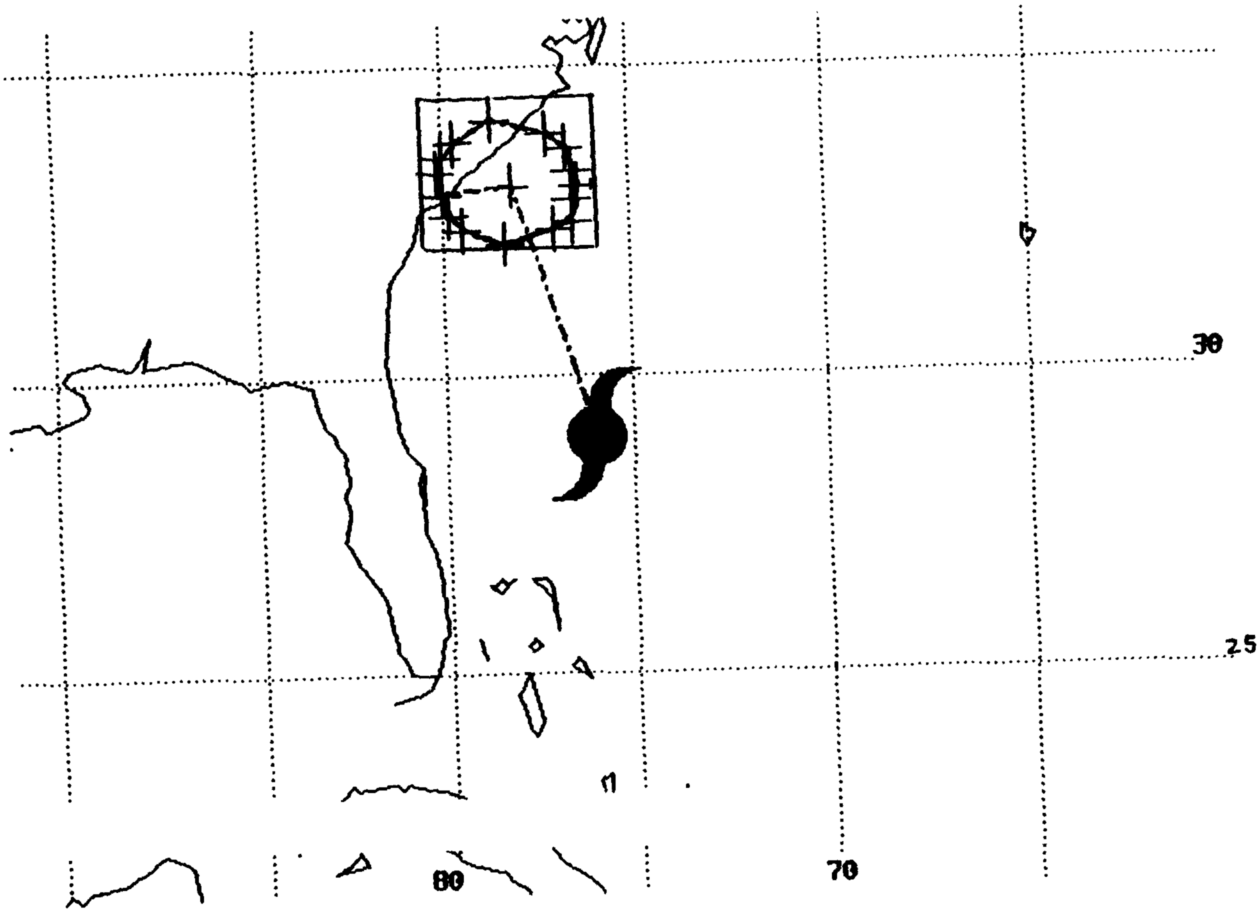


Figure 1. Probability Ellipse With Corresponding Probability Rectangle

3.2.3 Landfall Prediction Regions. The idea of landfall prediction is to determine the probability that a storm will make landfall in a given section of coast. An obvious approach based on our Monte Carlo simulation is to run the model numerous times from a position offshore and keep track of the proportion of tracks that cross a given section of coast. This proportion provides an estimate of the probability that a storm will make landfall in that region. Generally, this will enable us to assess the location of landfall, but not its exact timing, however. Predicting the time of landfall (within a margin of a few hours) is not as important as predicting the area affected for effective evacuation.

Another approach is to note the coastal area "covered" when a prediction ellipse intersects the coast. Varying the significance level, α, will generate contours of equal probability which intersect different sections of coast and provide an idea of the likelihood of landfall at a particular location.

The more accurate the a model is, the more accurate the forecast it gives. The next chapter presents our efforts to improve the time series model by attempting to identify potential outliers in the data.

IV. Examination of Anomalous Storms

This chapter presents the results of attempts made to identify possible modifications to Mott's model that could potentially be made to improve its forecast accuracy.

4.1 Identifying Anomalous Storms

Curry and Mott commented on the possible impact of anomalous, or outlier, data on the statistical results of their respective models. Outliers introduce potentially significant hidden bias into the models because it is difficult to determine if a particular storm will generally fit the model ahead of time. This research effort is aimed at identifying and characterizing apparently anomalous storms in order to determine if they have any common characteristics which could be exploited to improve the forecast model. The storms were ranked according to forecast error, then resulting patterns were analyzed.

4.1.1 Ranking Forecast Errors. One approach to identifying outliers is to rank the forecasts by magnitude of error and identify storms with the largest errors. For example, storms with forecast errors of greater than, say, three standard deviations above the mean forecast error could be classified as potentially anomalous since one normally expects only about 1% of all forecast errors to exceed this value. If outliers could be identified early in their life, they could be modeled separately. Our intent is to eventually remove outliers from the data base and recompute the model coefficients. The resulting model would potentially have greater accuracy by removing the bias introduced by anomalous storms.

In this research, storms were ranked according to the magnitude of their average and maximum 24– and 72–hour forecast errors. After ranking, the tracks of some storms with an error greater than three standard deviations above the mean

were plotted to view their behavior. Most outliers exhibited eccentric tracks, some looping and others accelerating beyond the model's ability to predict them. Others tended to move, often rapidly, from west to east while the storms that were forecast best tended to move steadily. Some of these tracks are plotted in Figure 2.

Tables 6 and 7 show the list of storms ranked by magnitude of forecast error. The format shows the ID number of the storm from the data base, the month and year of occurrence, maximum error during the storm, and average error during the storm. A cursory inspection, in response to Mott's conjecture that outliers may tend to be either early season or late season storms, shows most storms with poor forecasts occurred after August. This, however, is not consistent since quite a few good forecasts occur after August, also. As well, the peak of storm activity occurs in September, so it should not surprising that most of the worst forecast errors are experienced during that time (18:203).

Histograms of the average and maximum errors were prepared in an effort to identify if there were any potential outliers that could be better modeled separately. These are shown as Figures 3 through 6. There did not seem to be a clear trend with the data available. In fact, the errors seemed to approximately follow normal distributions. The expected pattern produced by outliers would show up as a peak further from the main concentration of errors, indicating a distinct group of forecast errors. The results show no such patterns, even when the resolution (range of errors) is changed. Another distinguishing characteristic might be those forecasts that lie outside of the prediction ellipse developed in the next section. That is, if a storm's position were to fall outside the 99% probability region, it could be considered a potential outlier and similar analysis could be done. Time constraints did not allow this to be accomplished for this thesis.

Other patterns of errors are not intuitively forthcoming. Evidently, factors other than those measured in the database are likely involved. It seems reasonable to assume that some meteorological factor or process drives outlier behavior that

cannot be modeled with data from the current database. With this result, our research ended.

Storm ID	Storm Date	Max Error	Avg Error
775	Oct 1975	406.37	123.81
847	Oct 1947	408.01	160.28
169	Aug 1969	408.57	144.95
651	Sep 1951	409.21	158.36
856	Nov 1956	4 11.24	230.84
581	Sep 1981	411.46	172.21
276	Aug 1976	412.49	150.08
572	Sep 1972	414.51	162.61
752	Oct 1952	417.06	114.14
350	Aug 1950	422.50	115.05
668	Sep 1968	430.35	215.19
854	Oct 1954	431.25	115.28
561	Sep 1961	431.64	98.38
354	Aug 1954	436.80	103.74
959	Oct 1959	443.21	155.97
461	Sep 1961	459.01	100.50
258	Aug 1958	462.57	152.64
851	Oct 1951	469.30	122.44
1061	Nov 1961	474.20	209.11
980	Oct 1980	479.23	157.52
849	Sep 1949	490.48	143.88
871	Sep 1971	501.67	85.97
1278	Nov 1978	515.69	252.87
470	Aug 1970	532.77	250.77
955	Sep 1955	546.17	116.77
1250	Oct 1950	604.81	157.60
481	Aug 1981	1205.31	182.48

Table 6. 24 Hour Ranked Errors

Storm ID	Storm Date	Max Error	Avg Error
778	Sep 1978	1016.37	451.82
1253	Oct 1953	1024.41	737.40
258	Aug 1958	1030.62	530.74
1058	Oct 1958	1032.94	415.17
367	Sep 1967	1043.50	377.25
450	Sep 1950	1045.85	319.91
958	Sep 1958	1050.38	645.49
553	Sep 1953	1060.15	691.55
572	Sep 1972	1061.29	817.39
651	Sep 1951	1130.37	580.13
172	May 1972	1136.55	812.74
650	Sep 1950	1188.04	377.25
1166	Nov 1966	1188.35	790.57
1061	Nov 1961	1200.92	717.42
467	Sep 1967	1206.40	677.32
665	Oct 1965	1226.99	514.65
673	Sep 1973	1227.87	568.29
149	Aug 1949	1240.87	949.23
748	Sep 1948	1282.29	578.41
561	Sep 1961	1285.91	403.93
863	Oct 1963	1288.61	525.64
1278	Nov 1978	1296.03	838.33
849	Sep 1949	1347.05	538.78
1145	Oct 1945	1347.68	1005.65
1469	Oct 1969	1369.30	605.66
653	Sep 1953	1423.60	1235.82
350	Sep 1950	1461.37	452.54
856	Nov 1956	1471.26	970.60
871	Sep 1971	1486.30	470.33
1255	Oct 1955	1501.15	1064.36
980	Oct 1980	1507.28	410.28

Table 7. 72 Hour Ranked Errors

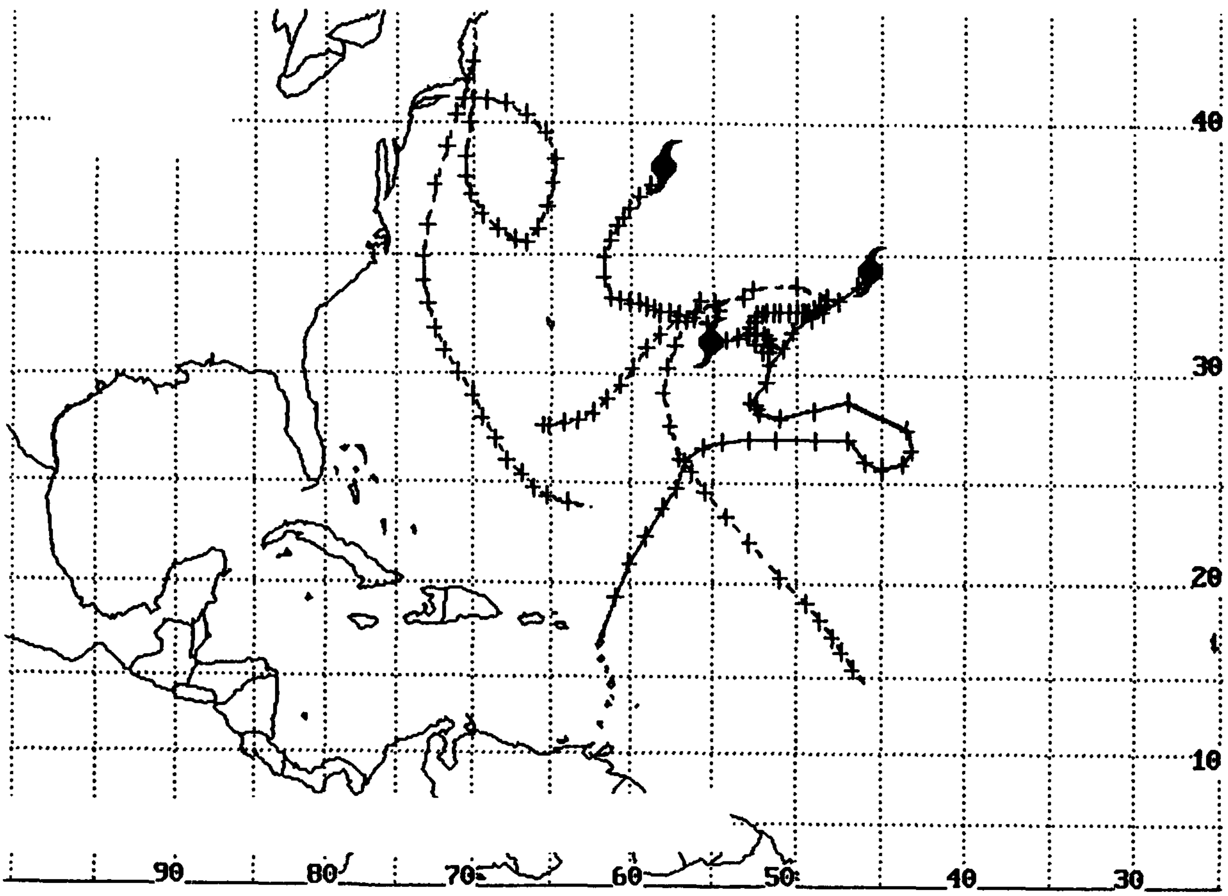
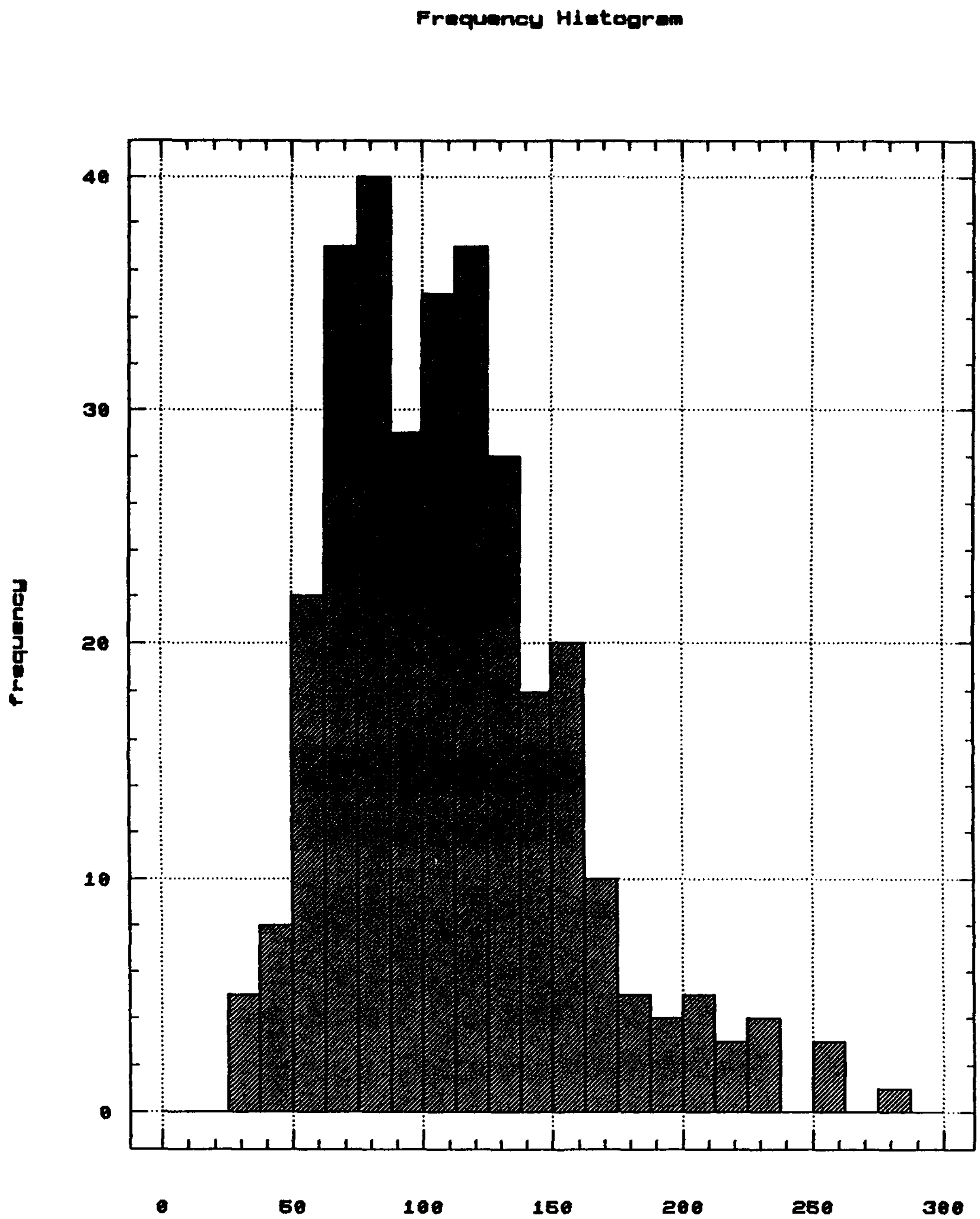


Figure 2. Anomalous Storm Tracks



Forecast Error, nmi

Figure 3. Histogram of 24 Hour Average Forecast Error

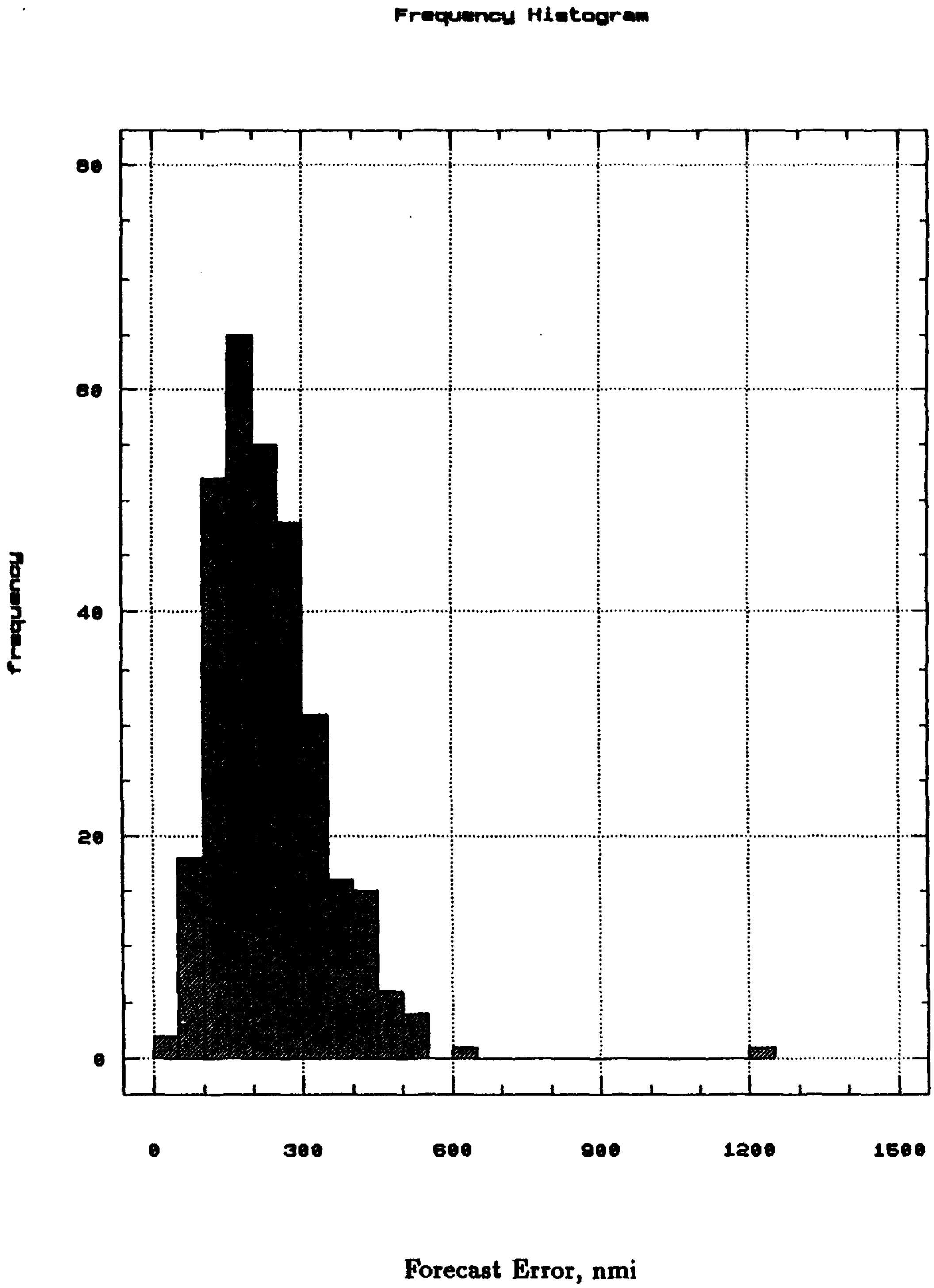
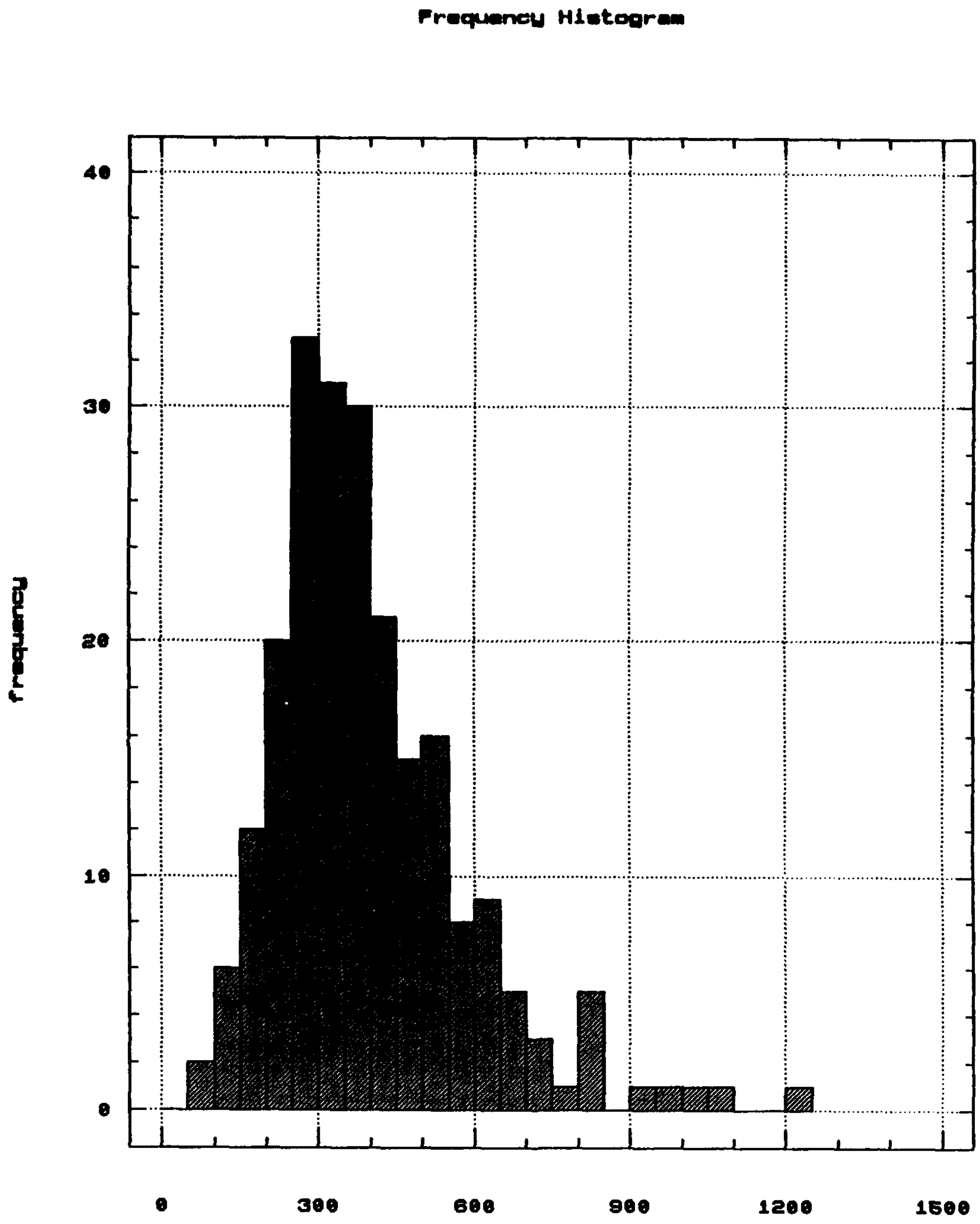
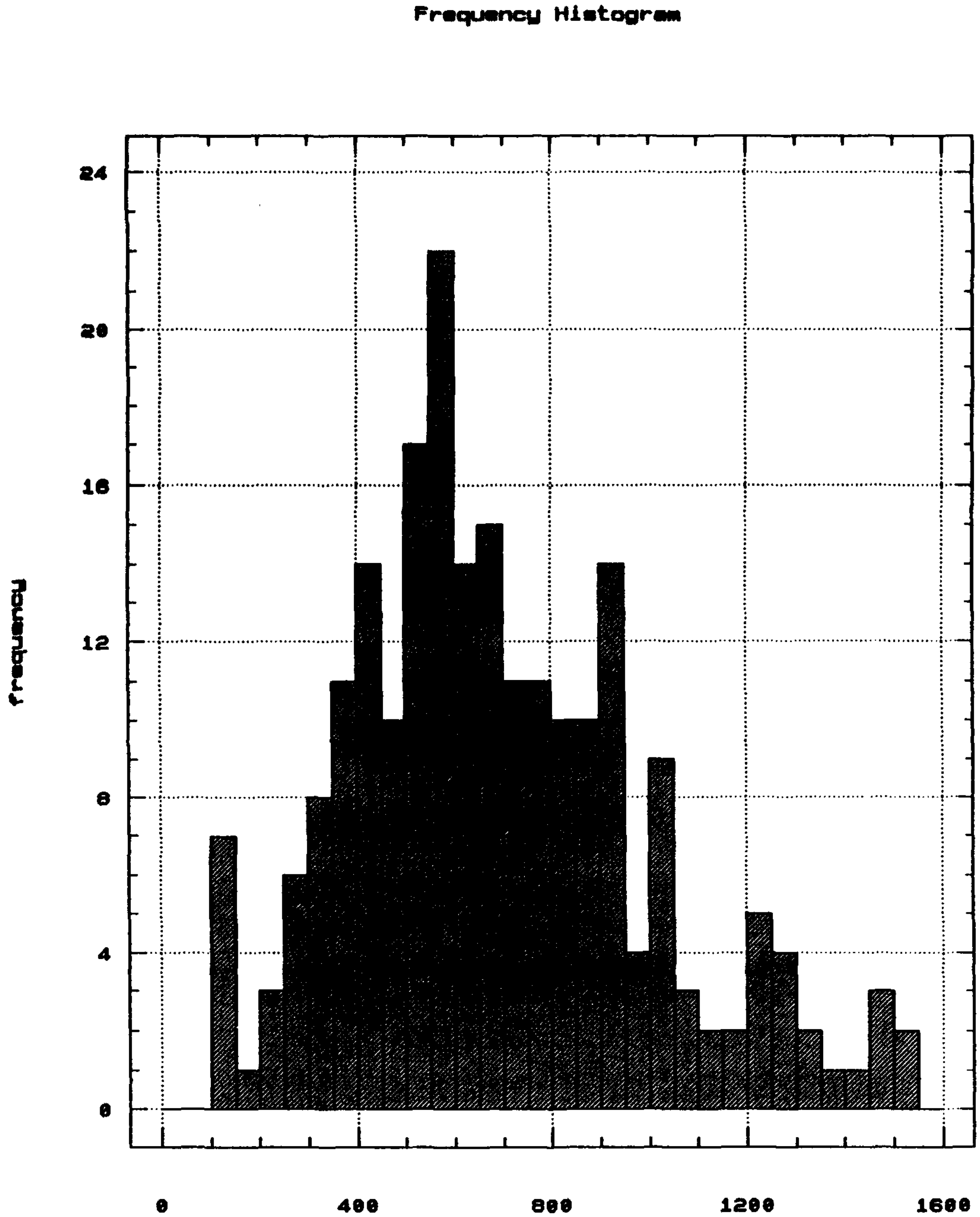


Figure 4. Histogram of 24 Hour Maximum Forecast Error



Forecast Error, nmi

Figure 5. Histogram of 72 Hour Average Forecast Error



Forecast Error, nmi

Figure 6. Histogram of 72 Hour Maximum Forecast Error

V. Summary and Conclusions

Curry initiated research on using a time series model to describe hurricane motion (3). Forecasts made with his model compare favorably with forecasts made by the NHC. Curry also developed a method of generating prediction ellipses as a means of describing an area where a storm might move, rather than just a potentially misleading point forecast.

Mott explored and improved the model; the best forecasts were made with the addition of a third parameter, wind speed.

A number of other researchers have added to the field of hurricane modeling and prediction. Two sources using statistical approaches point out that linear regression models are not effective for predicting hurricane motion or intensity, even with a variety of variables (7) (11). Most other researchers have explored meteorological aspects to varying degrees. Despite better computers and more extensive input data, the result of meteorological research seems to be a gradually decreasing rate of improvement in forecasting ability, as measured by forecast errors.

Both Curry and Mott suggest that their models could be biased by outlier data and that identification of potential outliers could lead to forecast improvement, possibly through the development of a separate model to handle outlier storms. Unfortunately, while outliers can be easily identified after the fact, there are as yet no objective criteria to apply as a storm occurs. Despite our efforts, we were unable to improve the situation, although we did establish that time of season does not seem to be a consistent indicator. This is an area where meteorological experts could apply their experience to suggest likely criteria to explore. Being able to separate outliers from "normal" storms should increase the accuracy of the time series model.

A time series model is ultimately limited because it does not account for the underlying meteorological processes driving hurricane development. But the surprising accuracy with such a simplistic model suggests it could have even better results

when coupled with a meteorological basis. Although there are opportunities for fine tuning the time series performance, such as increasing the number of latitude bands, the greatest improvement may lie in exploring meteorological avenues.

Development of prediction ellipses, especially for landfall prediction was one of our goals. Curry's ψ method would provide a straightforward solution, except some of the quantities needed, namely covariances, are not easily obtained or estimated. Applying the ψ method to Mott's model would be arduous and prone to errors. The Monte Carlo approach was conceptually easier to accomplish and the results are materially the same as from Curry's method. (One change from Curry's formulation is our use of a Chi-square critical value, rather than one from a standard normal distribution.) Using Mott's final model for greatest applicability, prediction ellipses give a quantitative measure of probability for a position forecast.

This approach can be used to generate landfall prediction zones when combined with fine resolution coastline information. The result is greater confidence in the bounds of an area at risk and attendant opportunity to minimize unnecessary evacuations.

Appendix A. Determining Tropical Cyclone Position and Intensity From Satellite Imagery

This appendix describes procedures used to determine tropical cyclone position and intensity from satellite imagery. This material is based on NOAA Technical Report NESDIS 11 (14) and a National Weather Association Meteorological Monograph (15).

Tropical meteorologists have been using satellite images for monitoring tropical storms for almost 25 years. Satellite imagery is important, especially at early storm development stages and in remote areas where weather measurements are otherwise unavailable. Satellites continue to carry more and better instruments as time goes on. Infrared (IR) and visible light sensors provide the primary sources of imagery, but microwave images and image processing will shortly provide enhanced capability and a greater variety of information.

Visual imagery is used whenever possible because of the relatively good resolution and imaging characteristics. Infrared images are important because they enable the analyst to monitor a storm's activity continuously night and day. The IR image of a tropical cyclone appears similar to that seen in a visual image of the same storm. In fact, the day by day changes in the cloud pattern can often be followed in the same way they are in visual imagery.

To determine reliable center coordinates from visible and IR imagery on a routine basis, a systematic approach is necessary. Such an approach is outlined in the following sections. It consists of five steps which are designed to help the analyst avoid common errors in tropical cyclone positioning when using satellite imagery.

The five steps are:

1. Locate the overall pattern center

2. Examine for small scale features

3. compare center location with forecast

4. Compare center with previous pattern center

5. Make final center adjustments

The first step is to determine the center of the overall cloud pattern of the tropical cyclone. This "first guess" estimate of the center is determined by one of two methods: either by locating the focal point of the broad scale cloud line and band curvature of the system, or by comparing the cloud pattern being analysed with patterns in the model of tropical cyclone development which includes the center placement for each pattern.

In the second step of the analysis procedure, the area around the pattern center found in step 1 is examined for small scale cloud feature indications that often give an improved center location. The third step is to compare the center arrived at in the first two steps with the extrapolated track (or forecast) position for the time of the satellite image. This step brings to light the possible errors due to wrong cloud center selection or due to displacements caused by vertical wind shear. It presumes that short period forecast positions are fairly accurate.

In the fourth step, the center placement in a previous storm and its relation to cloud features is compared with the current center placement relative to similar cloud features. This step is important when step three reveals a possible location error. The fifth step involves possible adjustments to the center location when indicated by either gridding errors, by high satellite viewing angles, or by the displacement of the cloud system center away from the surface wind center of the cyclone.

The confidence one places in the center location depends on four primary factors. They are: the type of cloud features defining the center, the vertical integrity of the vortex, the grid accuracy, and the type of imagery used in the analysis. When using enlarged visible pictures with accurate gridding, the following guidelines are recommended:

1) For low level cloud lines defining a tight center and for well-defined eyes, the accuracy is comparable to that of reconnaissance locations ($\pm 0.2^{\circ}$ latitude).

2) For tightly curved upper level features and moderately defined low level features, accuracies of $\pm 0.3^{\circ}$ latitude are expected.

3) For multiple center patterns and sheared patterns, average errors of 0.4° latitude or 24 nmi are to be expected. For this last category of patterns, it should be remembered that multiple wind and pressure centers may also involve errors in the verification data.

4) The confidence ratings listed above in 2) and 3) should be lowered for IR (without eyes), and for cloud systems beginning to show the effects of strong vertical shear.

Additional technical details are contained in the references and they should be consulted for further information.

Appendix B. The Time Series Models

B.1 Curry's Model

Curry found the second, third, and fifth coefficients were small, so he dropped them from his model. The following tables show the coefficients he reported, separated by latitude band.

$10^\circ - 15^\circ$				
.696			.101	
.233			-.075	
.607			.251	

$15^\circ - 20^\circ$				
.766			-.106	
-.010			.014	
.012			-.050	
.775			.088	

$20^\circ - 25^\circ$				
.849			.013	
-.064			.073	
.026			-.052	
.779			.121	

$25^\circ - 30^\circ$				
.777			.016	
-.101			.083	
.103			-.198	
.837			.032	

$30^\circ - 35^\circ$				
.746			-.015	
-.049			-.011	
.050			-.030	
.841			.068	

$35^\circ - 40^\circ$				
.735			-.094	
-.075			.023	
.030			-.005	
.881			-.006	

40° – 45°				
.742			.013	
-.067			-.003	
-.145			.125	
.831			-.042	

Latitude Band	Constants	
	C_1	C_2
10° – 15°	.048	.127
15° – 20°	.053	.139
20° – 25°	.054	.067
25° – 30°	.071	.052
30° – 35°	.072	-.044
35° – 40°	.087	-.109
40° – 45°	-.086	-.205

B.2 Mott's Model

Equations 7-9 show the form of Mott's model. The following table gives the ϕ coefficients by latitude band. The first row lists the five latitude–latitude ($\phi_{11,n}$) coefficients, the second row lists the latitude–longitude ($\phi_{12,n}$) coefficients, the third row lists the latitude–wind speed ($\phi_{13,n}$) coefficients. The fourth through sixth rows list the longitude–$\cdots$ coefficients and the seventh through ninth rows list the wind speed–$\cdots$ coefficients.

$10^o - 15^o$				
.766	.107		.088	-.143
-.105	.054			.038
.002	-.002			
.136			-.179	.109
.840		.116		
-.001				
1.457			.622	
1.516	-.530			

$15^o - 20^o$				
.954	-.063			
	-.034			.039
.001		-.001		
.855				.075
	-.005	.005		
1.449	-.425		-.056	

$20^o - 25^o$				
.880			.075	-.087
-.206	.078	.065		.030
-.383	.251			
.634	.093	.119	.065	
1.529				
1.432	-.464			

$25^o - 30^o$				
1.036	-.158		.068	-.079
-.114		.098		
		.002	-.002	
			-.078	
1.049		-.142	.064	-.063
	.001			
				.389
1.409	-.399		-.100	.045

30° − 35°				
1.081	-.253	.138	-.073	
-.053		.051		
.001				
-.049				-.056
1.102	-.073	-.081		-.043
				.422
1.334	-.224	-.156		

35° − 40°				
1.132	-.193			
-.057			.129	-.066
		-.129		
1.126	-.246			-.078
	.005		-.005	
1.359	-.264	-.142		

40° − 45°				
.996				-.137
		-.070	.065	
.183	-.208			
1.062	-.152	.106		-.218
-.006			.015	-.013
1.163	-.103	-.167		

Latitude Band	Constants		
	C_1	C_2	C_3
10° − 15°	.065	.085	.586
15° − 20°	.044	.049	2.116
20° − 25°	.091	.058	1.817
25° − 30°	.066	-.057	2.748
30° − 35°	.019	-.039	2.825
35° − 40°	.079	-.103	2.380
40° − 45°	.029	-.153	4.300

Appendix C. Monte Carlo FORTRAN Code to Generate Probability Ellipse

```
C MONTE.FOR
C
C A PROGRAM TO GENERATE HURRICANE PROBABILITY
C ELLIPSES USING MONTE CARLO SIMULATION
C
      INTEGER J, K, I, M, NSTEP, NPOINT, L
      REAL LATDEV,LONDEV,A1,A2,A3,LALORHO,COVSUM,DISC
      REAL COEF(16,14),COEF2(16,7),COV13(7),COV23(7)
      REAL LATSUM,LONSUM,WSSUM,LATRND,LONRND,WSRND,CHI
      REAL LATMEAN,WSMEAN,LONMEAN,LATVAR,LONVAR,LASTEP
      REAL RHO12(7), RHO13(7), RHO23(7)
      REAL FORE(1000,60), PLOTLAT(1000), PLOTLON(1000)
      REAL LALOCOV,COV12(7),LATMSE(7),LONMSE(7),WSMSE(7)
      REAL*8 SEED
      CHARACTER*20 OLDFIL, NEWFL

C ***** MEAN SQUARED ERRORS FROM MOTT'S RESULTS
        DATA LATMSE/.025,.033,.079,.065,.087,.124,.239/
        DATA LONMSE/.046,.071,.206,.112,.137,.192,.479/
        DATA WSMSE/21.43,35.21,40.67,34.53,18.41,18.7,23.43/
DATA COV12/7*0./
DATA COV13/7*0./
DATA COV23/7*0./
SEED=1234567
NPOINT=5
```

```
C *****  OPEN FILE FOR OUTPUT DATA
WRITE(*,250)
250 FORMAT(X,'INPUT FILENAME FOR ELLIPSE DATA')
READ(*,'(A20)') NEWFL
OPEN(30, FILE=NEWFL, STATUS='NEW')

C ***** GETTING 6 DATA POINTS TO FORECAST FROM
DO 680 I=0,6
WRITE(*,670) I
READ *, FORE(1,7-I)
WRITE(*,671) I
READ *, FORE(1,27-I)
WRITE(*,672) I
READ *, FORE(1,47-I)
WRITE(30,739) I
WRITE(30,740) FORE(1,7-I),FORE(1,27-I),FORE(1,47-I)
 DO 675 J=2,NPOINT
 FORE(J,7-I)=FORE(1,7-I)
 FORE(J,27-I)=FORE(1,27-I)
 FORE(J,47-I)=FORE(1,47-I)
675  CONTINUE
680 CONTINUE
WRITE(30,741)
670 FORMAT(X,'INPUT LATITUDE AT TIME T-',I1)
671 FORMAT(X,'INPUT LONGITUDE AT TIME T-',I1)
672 FORMAT(X,'INPUT WIND SPEED AT TIME T-',I1)
739 FORMAT(X,'OBSERVED INPUTS FOR TIME T-',I1)
```

```
740 FORMAT(3(2X,F6.2))
741 FORMAT(' ')

C ***** GET THE MATRIX THAT HAS THE FORECASTING COEFFICIENTS
      WRITE (*,501)
501   FORMAT(X,'FILE NAME OF MATRIX WITH THE FORECASTING COEFFICIENTS?')
      READ(*,'(A20)') OLDFIL
      OPEN(UNIT=24,FILE=OLDFIL,STATUS='OLD',IOSTAT=IERROR,ERR=500)
      DO 510 M = 1,16
        READ(24,*,END=520) COEF(M,1), COEF(M,2), COEF(M,3),
     +  COEF(M,4), COEF(M,5), COEF(M,6), COEF(M,7), COEF(M,8),
     +  COEF(M,9), COEF(M,10), COEF(M,11), COEF(M,12), COEF(M,13),
     +  COEF(M,14)
510   CONTINUE
520   CLOSE(24)
      GO TO 900
500   WRITE(*,507)IERROR
507   FORMAT('*** CANNOT OPEN FILE ***',I8)

C ***** GET COEFFICIENTS FOR PREDICTING WS
900   WRITE (*,901)
901   FORMAT(1X,'FILE NAME OF MATRIX WITH THE WS COEFFICIENTS?')
      READ(*, '(A20)') OLDFIL
      OPEN(UNIT=44,FILE=OLDFIL,STATUS='OLD',IOSTAT=IERROR,ERR=999)
      DO 910 M = 1,16
        READ(44,*,END=920) COEF2(M,1), COEF2(M,2), COEF2(M,3),
     +  COEF2(M,4), COEF2(M,5), COEF2(M,6), COEF2(M,7)
910   CONTINUE
```

```
920   CLOSE(44)
      GO TO 922
999   WRITE(*,907)IERROR
907   FORMAT('*** CANNOT OPEN WS FILE ***',I8)

C *****  GENERATE SIMULATED VALUES
C *****  (NSTEP SIX HOUR PERIODS AHEAD)
922     LATSUM=0
LONSUM=0
WSSUM=0
RHO12(K)=COV12(K)/(LATMSE(K)*LONMSE(K))
RHO13(K)=COV13(K)/(LATMSE(K)*WSMSE(K))
RHO23(K)=COV23(K)/(LONMSE(K)*WSMSE(K))
NSTEP=4

DO 300 I=1,NPOINT
 DO 560 J=1,NSTEP

C *****  GET PROPER LATITUDE BAND FOR FORECAST MODEL
       K=0
        IF(FORE(I,6+J).LT.15.0)K=1
        IF((FORE(I,6+J).LT.20.0).AND.(FORE(I,6+J).GE.15.0))K=2
        IF((FORE(I,6+J).LT.25.0).AND.(FORE(I,6+J).GE.20.0))K=3
        IF((FORE(I,6+J).LT.30.0).AND.(FORE(I,6+J).GE.25.0))K=4
        IF((FORE(I,6+J).LT.35.0).AND.(FORE(I,6+J).GE.30.0))K=5
        IF((FORE(I,6+J).LT.40.0).AND.(FORE(I,6+J).GE.35.0))K=6
        IF(FORE(I,6+J).GE.40.0)K=7
```

```
C *****  RANDOM ERROR GENERATION
R=RANDOM(SEED)
S=RANDOM(SEED)
T=RANDOM(SEED)
LATRND=(R**.1349-(1-R)**.1349)/.1975
LONRND=(S**.1349-(1-S)**.1349)/.1975
WSRND=(T**.1349-(1-T)**.1349)/.1975
A1=LATRND*LATMSE(K)
A2=LATRND*LONMSE(K)*RHO12(K)+LONRND*LONMSE(K)*SQRT(1-RHO12(K)**2)
A3=LATRND*WSMSE(K)*RHO13(K)+LONRND*WSMSE(K)*(RHO23(K)-RHO12(K)
     +    *RHO13(K))/SQRT(1-RHO12(K)**2)+WSRND*WSMSE(K)*SQRT((1
     +    -RHO12(K)**2)*(1-RHO13(K)**2)-(RHO23(K)-RHO12(K)
     +    *RHO13(K))**2)/SQRT(1-RHO12(K)**2)

C ***** FORECAST LATITUDE USING INPUTTED FORECAST MODEL COEFFICIENTS
      FORE(I,7+J)=FORE(I,6+J)
     ++COEF(1,K)*(FORE(I,6+J)-FORE(I,5+J))
     ++COEF(2,K)*(FORE(I,5+J)-FORE(I,4+J))
     ++COEF(3,K)*(FORE(I,4+J)-FORE(I,3+J))
     ++COEF(4,K)*(FORE(I,3+J)-FORE(I,2+J))
     ++COEF(5,K)*(FORE(I,2+J)-FORE(I,1+J))
     ++COEF(6,K)*(FORE(I,26+J)-FORE(I,25+J))
     ++COEF(7,K)*(FORE(I,25+J)-FORE(I,24+J))
     ++COEF(8,K)*(FORE(I,24+J)-FORE(I,23+J))
     ++COEF(9,K)*(FORE(I,23+J)-FORE(I,22+J))
     ++COEF(10,K)*(FORE(I,22+J)-FORE(I,21+J))
     ++COEF(11,K)*(FORE(I,46+J))
     ++COEF(12,K)*(FORE(I,45+J))
```

```
     ++COEF(13,K)*(FORE(I,44+J))
     ++COEF(14,K)*(FORE(I,43+J))
     ++COEF(15,K)*(FORE(I,42+J))
     ++COEF(16,K)+A1

C ***** FORECAST LONGITUDE USING INPUTTED FORECAST MODEL COEFFICIENTS
      FORE(I,27+J)=FORE(I,26+J)
     ++COEF(1,K+7)*(FORE(I,6+J)-FORE(I,5+J))
     ++COEF(2,K+7)*(FORE(I,5+J)-FORE(I,4+J))
     ++COEF(3,K+7)*(FORE(I,4+J)-FORE(I,3+J))
     ++COEF(4,K+7)*(FORE(I,3+J)-FORE(I,2+J))
     ++COEF(5,K+7)*(FORE(I,2+J)-FORE(I,1+J))
     ++COEF(6,K+7)*(FORE(I,26+J)-FORE(I,25+J))
     ++COEF(7,K+7)*(FORE(I,25+J)-FORE(I,24+J))
     ++COEF(8,K+7)*(FORE(I,24+J)-FORE(I,23+J))
     ++COEF(9,K+7)*(FORE(I,23+J)-FORE(I,22+J))
     ++COEF(10,K+7)*(FORE(I,22+J)-FORE(I,21+J))
     ++COEF(11,K+7)*(FORE(I,46+J))
     ++COEF(12,K+7)*(FORE(I,45+J))
     ++COEF(13,K+7)*(FORE(I,44+J))
     ++COEF(14,K+7)*(FORE(I,43+J))
     ++COEF(15,K+7)*(FORE(I,42+J))
     ++COEF(16,K+7)+A2

C ***** FORECAST WIND SPEED USING INPUTTED FORECAST MODEL COEFFICIENTS
      FORE(I,47+J)=COEF2(1,K)*(FORE(I,6+J)-FORE(I,5+J))
     ++COEF2(2,K)*(FORE(I,5+J)-FORE(I,4+J))
     ++COEF2(3,K)*(FORE(I,4+J)-FORE(I,3+J))
```

```
     ++COEF2(4,K)*(FORE(I,3+J)-FORE(I,2+J))
     ++COEF2(5,K)*(FORE(I,2+J)-FORE(I,1+J))
     ++COEF2(6,K)*(FORE(I,26+J)-FORE(I,25+J))
     ++COEF2(7,K)*(FORE(I,25+J)-FORE(I,24+J))
     ++COEF2(8,K)*(FORE(I,24+J)-FORE(I,23+J))
     ++COEF2(9,K)*(FORE(I,23+J)-FORE(I,22+J))
     ++COEF2(10,K)*(FORE(I,22+J)-FORE(I,21+J))
     ++COEF2(11,K)*(FORE(I,46+J))
     ++COEF2(12,K)*(FORE(I,45+J))
     ++COEF2(13,K)*(FORE(I,44+J))
     ++COEF2(14,K)*(FORE(I,43+J))
     ++COEF2(15,K)*(FORE(I,42+J))
     ++COEF2(16,K)+A3

WRITE(30,729) I,J
WRITE(30,730) FORE(I,7+J),FORE(I,27+J),FORE(I,47+J),
     +                 A1,A2,A3
WRITE(30,741)
560       CONTINUE
 LATSUM=LATSUM+FORE(I,7+NSTEP)
 LONSUM=LONSUM+FORE(I,27+NSTEP)
 WSSUM=WSSUM+FORE(I,47+NSTEP)
    WRITE(*,710) LATSUM,LONSUM,WSSUM
300  CONTINUE
WRITE(30,741)
710 FORMAT(3(X,F8.2))
729 FORMAT(X,'AT NPOINT ',I2,' AND NSTEP ',I2,
     +  ' FORECAST VALUES ARE:')
```

```
730 FORMAT(X,'LAT-',F5.2,' LON-',F6.2,' WIND-',F6.2,
     +   ' RANDOM ERRORS ARE',2(2X,F6.4),2X,F7.3)

C *****   CALCULATING SAMPLE DEVIATIONS, COVARIANCE,
C *****   AND CORRELATION OF FORECAST DATA
LATMEAN=LATSUM/NPOINT
LONMEAN=LONSUM/NPOINT
WSMEAN=WSSUM/NPOINT
WRITE(*,667)
667 FORMAT(X,'FINISHED WITH FORECASTING')
DO 578 L=1,NPOINT
 LATVAR=(LATMEAN-FORE(L,7+NSTEP))**2+LATVAR
 LONVAR=(LONMEAN-FORE(L,27+NSTEP))**2+LONVAR
 COVSUM=(LATMEAN-FORE(L,7+NSTEP))
     +          *(LONMEAN-FORE(L,27+NSTEP))+COVSUM
578   CONTINUE
WRITE(30,750) LATMEAN,LONMEAN,LATVAR,LONVAR
WRITE(30,741)
 LATDEV=(LATVAR/NPOINT)**.5
 LONDEV=(LONVAR/NPOINT)**.5
 LALOCOV=COVSUM/NPOINT
 LALORHO=LALOCOV/(LATDEV*LONDEV)
LATVAR=LATVAR/NPOINT
LONVAR=LONVAR/NPOINT
750 FORMAT(X,'LATMEAN=',F6.2,'  LONMEAN=',F6.2,'  LATVAR=',
     +          F6.3,'  LONVAR=',F6.3)

C ***** POINTS ON ELLIPSE CALCULATION
```

```
CHI=9.21
L=0
LASTEP=0.
219 DISC=(1.-LALORHO**2)*(CHI-LASTEP**2)
PLOTLAT(L)=LATMEAN+LASTEP*LATDEV
PLOTLON(L)=LONMEAN+LONDEV*(LALORHO*LASTEP+SQRT(DISC))
L=L+1
LASTEP=LASTEP+.2
IF(LASTEP**2.LE.CHI) GOTO 219
220 LASTEP=LASTEP-.2
IF(LASTEP**2.GT.CHI) GOTO 221
DISC=(1.-LALORHO**2)*(CHI-LASTEP**2)
PLOTLAT(L)=LATMEAN+LASTEP*LATDEV
PLOTLON(L)=LONMEAN+LONDEV*(LALORHO*LASTEP-SQRT(DISC))
L=L+1
GOTO 220
221 LASTEP=LASTEP+.2
IF(LASTEP.GT.0.) GOTO 222
DISC=(1.-LALORHO**2)*(CHI-LASTEP**2)
PLOTLAT(L)=LATMEAN+LASTEP*LATDEV
PLOTLON(L)=LONMEAN+LONDEV*(LALORHO*LASTEP+SQRT(DISC))
L=L+1
GOTO221

C ***** OUTPUT ELLIPSE POINTS TO A FILE
222 WRITE(30,720)
  DO 215 I=0,L-1
   WRITE(30,270) PLOTLAT(I),PLOTLON(I)
```

```
215   CONTINUE
CLOSE(30)
720 FORMAT(2X,'LAT',4X,'LON')
270 FORMAT(X,2(X,F6.2))
         END

FUNCTION RANDOM(SEED)
 REAL*8 PROD, SEMI, SEED
 PROD=16807.D0*SEED
 SEMI=DMOD(PROD,2147483647.D0)
 RANDOM=SEMI*0.4656613E-9
 SEED=SEMI
RETURN
       END
```

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In this thesis, a class of time series models for forecasting a hurricane's future position based on its previous positions and a generalized model of hurricane motion are examined and extended.
Results of a literature review suggest that meteorological models continue to increase in complexity while few statistical approaches, such as linear regression, have been successfully applied. An exception is provided by a certain class of time series models that appear to forecast storms almost as well as current meteorological models without their tremendous complexity.
A suggestion for enhancing the performance of these time series models is pursued through an examination of the forecast errors produced when these models are applied to historical storm tracks. The results uncover no patterns that can be exploited in developing an improved model and suggest that there are meteorological processes or factors at work beyond those that can be modeled with the current data.
The statistical structure of the time series approach is exploited to develop a practical method for determining prediction regions which probabilistically describe a hurricane's likely future position using a Monte Carlo simulation.

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